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Building information modeling based building design optimization for sustainability

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ABSTRACT

Environmental problems, especially climate change, have become a serious global issue waiting for people to solve. In the construction industry, the concept of sustainable building is developing to reduce greenhouse gas emissions. In this study, a building information modeling (BIM) based building design optimization method is proposed to facilitate designers to optimize their designs and improve buildings' sustainability. A revised particle swarm optimization (PSO) algorithm is applied to search for the trade-off between life cycle costs (LCC) and life cycle carbon emissions (LCCE) of building designs. In order to validate the effectiveness and efficiency of this method, a case study of an office building is conducted in Hong Kong. The result of the case study shows that this method can enlarge the searching space for optimal design solutions and shorten the processing time for optimal design results, which is really helpful for designers to deliver an economic and environmental-friendly design scheme.

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1. Introduction

Nowadays, the construction industry has become the third largest contributor of greenhouse gas emissions to the environment. Over 70% of the greenhouse gases are emitted from buildings [1]. Buildings also consume 70% of the energy in the U.S. Considering that climate change is getting worse, to reduce the emission loads of greenhouse gases, especially carbon emissions, of buildings becomes a top priority of the construction industry. On the other hand, tighter budgets and higher customer expectations have brought more pressure on project participants than ever before to control the LCC [2]. In this situation, methods which can improve the sustainability of a building while minimizing the LCC have drawn increasing attention in recent years. One of the useful methods is developing sustainable buildings.

Making good design decisions at the initial stage plays an important role in realizing sustainable buildings. An investigation by Rebitzer [3] indicated that although design itself does not induce many environmental impacts, it determines nearly 70% of the environmental impacts over the whole lifetime of a building. Not only can energy be saved by applying sustainable buildings, LCC of buildings can also be reduced. Kats [4] made a statistical analysis of green building costs and financial benefits in the U.S. It showed that comparing with the conventional buildings, a sustainable building with 20-year lifetime has the benefit of \$50–66/ft^2. Obviously, the better designs are made, the more economic and environmental-friendly projects will be. In recent years, BIM has become a popular approach used for sustainable building design. It simulates a construction project in the virtually visible environment. All the related information, including geometry, spatial relationships, geographic information, and quantities and properties of building elements, is saved in its model [5]. Therefore, BIM provides an ability to do the simulation for verifying the performance of design schemes. The use of BIM enables designers to improve their designs and select the optimal one.

This study aims to develop a BIM based multi-objective optimization model, facilitating designers to identify and choose the optimal carbon emission and cost trade-off design scheme for their clients.

Abbreviations: BIM, building information modeling; PSO, particle swarm optimization; LCC, life cycle cost; LCCE, life cycle carbon emission; HVAC, heating ventilating and air conditioning; DF, daylight factor; DA, daylight autonomy; COP, coefficient of performance; AED, annual energy demand; CEF, carbon emission factor; WBS, work breakdown structure.

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2. Building design methods

2.1. Development of sustainable building design methods

The theme of sustainable building is not to deplete resources, disturb ecosystems, or disrupt natural life rhythms during design, construction, operation, maintenance and demolition of a building. Since it is inevitable to carry out human activities with some negative influence on the environment and building itself, the adoption of sustainable buildings tends to cut down as many negative impacts as possible. Design is a central element of sustainable building practice. Since 1990s, sustainable building design methods have been increasingly accepted by designers, engineers and researchers in the construction industry. Generally, sustainable building design methods fall into three major categories.

Initially, rules and guidelines are used by people to examine and weigh the sustainability of designs. The empirical rules or guidelines are generalized statements, tables or diagrams that can guide decision-making for good design [6]. These principles can be easily applied and do not require many complex techniques or time-consuming procedures. Butera [7] compared resources and energy consumption structures of cities in developing and developed countries, and suggested that in order to improve the efficiency of building performance, sustainable design solutions should be differentiated in developing and developed countries. Tam et al. [8] proposed a system called "green construction assessment" to improve the environmental performance of the construction process in Hong Kong, in which different weightings of management performance indicators and operational performance indicators are summarized for designers and project managers as references to refine their own projects. Besides sharing knowledge and experience, taking a small model to provide data, knowledge, and experience for the industry and society was identified by Seyfang [9] as a good way to enhance building sustainability. Currently, the commonly used guideline is green building rating system. Since the Building Research Establishment Environmental Assessment Method (BREEAM) was first established in UK in 1992, many countries and territories have formed their own standards, for example, Leadership in Energy and Environmental Design (LEED) in the U.S., and Hong Kong Building Environmental Assessment Method (HK-BEAM). These standards are useful to evaluate the performance of a completed building. However, how to design a sustainable building and enable it to reach the design criteria has never been introduced by any building environmental assessment methods.

The increasing complexity of building designs with the development of building structures, materials, equipment indicates that only simple rules and guidelines cannot fulfil the requirements of current projects. In order to obtain more accurate data, many related elements, such as climate information, interactions among building subsystems and the architectures around, should be considered as well. Therefore, trial-and-error methods are applied to predict the performance of specific designs. Many studies attempt to reduce carbon emissions and energy consumptions by selecting proper building materials. For example, González and Navarro [44] calculated the carbon emission and embodied energy of some alternative materials in the same unit, and the ones with lowest values are picked out to compose new designs. Comparing with the original designs, LCCE of the new ones can be reduced up to 30%. However, González and Navarro [44] did not take the costs of materials into consideration. Besides building materials, some other factors are also studied. In the envelope design method proposed by Cheung et al. [10], six important design factors: insulation, thermal mass, glazing type, window size, color of external wall and external shading devices, are tested one by one. The values that lead to the least energy consumption of the factors are combined together to compose a new design. This method can save 31.4% of annual required cooling energy. Studies on lighting performance can also use trial-and-error methods. For example, Reinhart et al. [11] selected four types of windows to test the illumination level through them. The four windows have the same size but different glazing types, sunshade locations, and blinds locations and sizes. The merits and demerits of each type of windows are obtained by comparing the values of dynamic daylighting metrics. Although trial-and-error methods have been applied to extract the relationships among essential factors, energy consumption and carbon emission of buildings, there are still some shortcomings that cannot be ignored. Firstly, since designers have to repeat the calculation steps until they get the one satisfying all the preset criteria, large workloads are required when using trial-and-error methods. Secondly, this kind of methods can only deal with one design at a time; and continuous factors cannot be processed. The limitations cause many important factors being ignored and the search space being narrowed down. Thirdly, large workloads lead to long processing time. Due to time limit, designers usually miss the best solutions. Therefore, it is difficult to obtain the optimal design by trial-and-error methods.

In order to solve the problems in the former mentioned methods, optimization design methods are generated. Optimization methods aim at searching for optimal solutions with respect to some predefined performance criteria [6]. By applying an optimization method, the result can lead to both an improved solution and a broader knowledge about design space [12]. Various kinds of optimization strategies have been proposed for building design improvement. Burger [13] used level set methods for the optimization of building shape design and reconstruction. Choudhary et al. [14] applied analytical target cascading, a multi-level engineering design optimization framework, to decompose energy analysis problems of a building into hierarchical levels. Since these methods heavily rely on some mathematical equations, the precision and reliability of their results are waiting for improvement. For this reason, simulation tools have been introduced into optimization design methods. In the investigation conducted by Wetter and Polak [55], BuiltOpt, a detailed building energy and daylight simulation program, was utilized to analyze the energy performance of buildings. Since multi-objective problems are met mostly in the real world, the artificial intelligence approach, which is popularly used in many other areas, has been applied for the improvement of sustainable building design. As a search heuristic that mimics the process of natural evolution, genetic algorithms (GA) have become a widespread optimization method. Many studies attempt to optimize the designs of building structure and envelope by means of GA so as to get the trade-off between cost and energy consumption of buildings ([15,16,56]). Considering that it takes time for the potential solutions to converge during optimization process, Magnier and Haghighat [17] exploited artificial neural network to characterize building behavior before using GA. As a result, the operation time can be reduced and the energy can be saved by up to 13%. GA is not the only effective way for sustainable building design; other multi-objective optimization methods are also competent for this work. In the strategy proposed by Rapone and Saro [18], PSO was taken to refine the curtain wall design of an office building with the aim of carbon emission reduction. Its results illustrated that this method is effective and universal adaptive. For all the optimization design methods, there are generally two common grounds: (1) for sake of boosting the searching speed for optimal solutions and improving the accuracy of results, simulation tools are deployed to interact with optimization algorithms; (2) discrete and continuous factors are all counted and the design space is enlarged, which enhance the reliability of the design schemes.

2.2. Limitations and shortcomings

The concept of sustainable building has been widely spread and practiced on many real projects all over the world. Although its effectiveness has been proved by real cases, there is still a long way for designers and engineers to go for improving building performance throughout the lifetime of buildings. Firstly, most of the design methods only focus on one objective, such as energy reservation, thermal performance, and carbon emission reduction. However, cost saving is a crucial target to clients. Therefore, multi-objective optimization methods which can reduce both the LCC and the LCCE need to be highlighted. Secondly, it is inevitable to have a larger number of computations when pursuing a higher precision of the optimal design scheme. For current design improvement methods, heavy workload and time consumption are two common shortcomings. As a result, designers expect a method with a higher efficiency and accuracy. Thirdly, since thermal performance consumes most of the energy in a building comparing with the other performance aspects, quite a number of studies are focused on the improvement of thermal performance. However, the other aspects like lighting performance also have significant impacts on the overall energy consumption of a building. Besides, different performance aspects in a building closely connect with each other. Changing one aspect will affect the others. Therefore, it is necessary to test the whole building and consider the interactions among different performance aspects during the design process.

In this study, a multi-objective optimization model is proposed for BIM-based sustainable building design. The proposed model overcomes the research problems mentioned above. Factors in relation to both thermal and lighting performance are considered in the proposed model. This study does not cover the heating, ventilating and air conditioning (HVAC) system. In this case, the plant system is assumed to have unlimited capacity and is capable of always keeping the temperature in the testing area stable during the periods of peak load [18].

3. Methodology

3.1. BIM

BIM is a hot topic in recent years and performs excellently in sustainable building designs [19]. According to the U.S. National BIM Standard [45], *BIM is a shared knowledge resource for information about a facility forming a reliable basis for decisions during its life-cycle; defined as existing from earliest conception to demolition.* BIM has not only a database saving and providing necessary information for projects, but also comprises many important functions for building performance analysis. Therefore, investigations of sustainable building design become easier and more systematic by means of BIM. Autodesk Revit's White Paper [41] indicated that inefficiencies, mistakes and delays accounted for almost one third of the annual total spending on construction in America. With the help of BIM, designers can predict the potential mistakes and inefficiencies and adjust the designs in time so as to reduce the risk and loss of project failure. Recent surveys show that 48% of the architectural offices in the U.S. already use methods of BIM [20]. In order to significantly improve its efficiency and effectiveness, the functions of modeling, simulation, analysis of thermal and lighting performance, and database in BIM are integrated in the sustainable building design process of this research.

3.2. Optimization method – PSO

Currently, many optimization methods have been developed to solve multi-objective optimization problems. Evolutionary algorithms (EAs) are popular among them because of their inherent parallelism and capability of exploiting similarities of solutions by recombination [21]. PSO has the same effect as EAs. PSO is characterized by the directed mutation, population representation and operators, etc., which distinguish it from the EAs. With its rapid development, many revised methods are presented and made up many deficiencies of PSO, making it more acceptable and applicable. The revised PSO method has proved the capability of obtaining the results as good as EAs with shorter time. Comparing with EAs, PSO is easier to be understood and programed. Considering that the model proposed in this study will be commonly used by designers, engineers and clients who may not be specialized in programming and computing, a revised PSO method is deployed in the proposed model to support the optimization system.

PSO is inspired by the social dynamics and emergent behavior that arises in socially organized colonies [22]. This population-based method is initialized by a population (with the name of *swarm*) of random solutions (with the name of *particles*) in a specific search scope. The particles "fly" randomly through the problem space by updating themselves with their own memories and social information gathered from the other particles [57]. Finally, they converge at the Pareto-optimal front after a series of processes. This algorithm can be described as follows ([23,24,58]):

If the position and velocity of the ith particle in the tth generation are denoted as $\boldsymbol{x}_t^i$ and v_t^i respectively, then in the next generation, its position $\boldsymbol{x}_{t+1}^i$ and velocity $\boldsymbol{v}_{t+1}^i$ can be displayed as:

$$\boldsymbol{v}_{t+1}^i = w\boldsymbol{v}_t^i + c_1 r_1 \left(\boldsymbol{p}_t^i - \boldsymbol{x}_t^i\right) + c_2 r_2 \left(\boldsymbol{g}_t^i - \boldsymbol{x}_t^i\right) \tag{1}$$

$$\boldsymbol{x}_{t+1}^i = \boldsymbol{x}_t^i + \boldsymbol{v}_{t+1}^i \tag{2}$$

where $i = 1,2,\ldots,S$; S is the size of the swarm; $t = 1,2,\ldots,N$; N is the sum of the generations; c_1 and c_2 are two positive constants, calling cognitive and social parameters; r_1 and r_2 are two random functions in the range [0,1]; $\boldsymbol{p}_t^i$ is the personal best of the ith particle till the tth generation; $\boldsymbol{g}_t^i$ is the global best of all the swarms so far; and w is the inertia weight applied to control the impact of the previous history of velocities on the current velocity, in order to influence the trade-off between the global and local exploration abilities of the particles. Learning from shared information is the way for the particles to reach their desired objectives. This is revealed in Eq. (1) by $(\boldsymbol{p}_t^i - \boldsymbol{x}_t^i)$ and $(\boldsymbol{g}_t^i - \boldsymbol{x}_t^i)$ which mean the best solution in each generation of the ith particle and the best solution among the swarms respectively [25]. The new position where the particle is "flying" to is expressed by Eq. (2). Then the performance of each particle is measured in accordance with a predefined objective function $f(\boldsymbol{x})$, which is related to the problem to be solved [23].

For a multi-objective problem, there is no explicit solution that can be defined as the "best" for all the objectives simultaneously. Instead, a Pareto-optimal solution set is obtained for decision makers to make the final decision. The searching and updating process of a two objective PSO problem can be illustrated by Fig. 1. According to Reyes-Sierra and Coello [53], an extra set called external archive in a different place of the swarms, which contains all the different leaders for the particle, has to be constructed. The external archive is a repository storing all the non-dominated solutions captured so far. When a particle is going to be updated, it chooses its leader from this external archive. In each process, the external archive has to be updated: the old leaders with dominance are replaced by a new one. As a result, the external archive can be reported as the ultimate output of the algorithm [26].

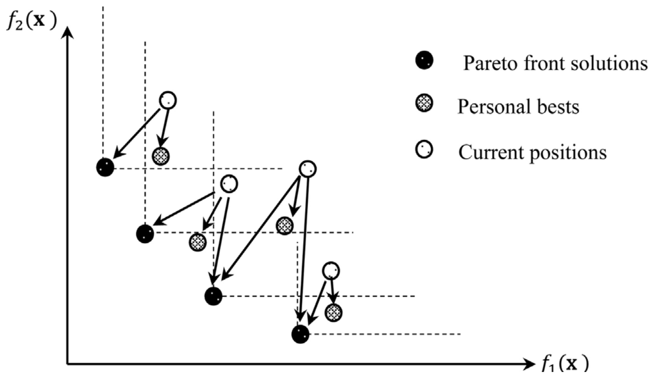

Fig. 1. PSO-based searching outline for Pareto-optimal solution set under two objectives (modified from [52,53]).

4. The proposed BIM based building design optimization model

Generally, the BIM-based building design optimization model is composed of two sections: BIM-based simulation and PSO-based optimization. Detailed operation procedures are illustrated in Fig. 2.

4.1. Building information model establishment

In this study, 3-D models of building deigns are developed in the BIM system. In this building information model, all the information related to the design, such as location, climate, and materials of the building, can be uploaded in the database. People can search for any data they need from this model. Therefore, the building information model provides more convenience to designers and saves much time during the design process.

The BIM software used in this study is *Ecoect Analysis* produced by Autodesk Inc. Its accuracy and effectiveness has been verified by many relevant studies, such as Marsh [27], Rogers [28], Yan et al. [29] and Sadafi et al. [30]. There are totally two categories of inputs. The initial design of a project along with the corresponding building materials has to be built at the beginning. Subsequently, project based information, including location of the project, local climate information, and the surrounding situations like number and height of the architectures around and shape of the construction site, has to be collected.

4.2. BIM-based simulation system

When the building information model is ready, it can be delivered to the BIM-based simulation system for building performance assessment. Both lighting performance and thermal performance of building designs have to be simulated and assessed.

4.2.1. Lighting performance simulation

Firstly, the designs in which daylight illumination levels do not fulfill the basic standard have to be screened out. The Daylight Factor (DF) used to assess the potential of a building design to provide useful levels of internal daylight illumination is applied in this step [31]. According to the investigations and green building guidelines in many countries and territories, such as HK-BEAM [32] and Reinhart et al. [11], the standard of 2% of DF in a room has been fixed as the basic sustainable level of the daylight illumination. Consequently, the lighting simulation engine assesses the DF of each design. Designs with less than 2% of DFs are deleted. The qualified alternatives are left for the following steps.

After DF assessment, the annual daylight illumination time of the qualified designs has to be calculated. The criterion at this step is Daylight Autonomy (DA), which is used to detect whether a space is luminous enough for the occupants to work or live with natural light along in the work hours. The Charted Institution of Building Services Engineers (CIBSE) recommended that a maintained illuminance of 500lux is appropriate for general offices [33]. Therefore, the time that the illumination is above 500lux in the daytime at the test point during one year is calculated and denoted as DA_{500} in this study. When daylight is not sufficient for the occupants, artificial lights are used to support the indoor illumination. Based on DA_{500}, the annual artificial lights working time can be calculated by Eq. (3):

$$T_{el-l} = (1 - DA_{500}) \times T_{day} \times T_{hour} \tag{3}$$

where T_{el-l} is the total amount of hours that artificial lights have to operate in a year; T_{day} is the number of working days per year; T_{hour} is the working hours per day.

Energy consumed by lighting system depends on the operation of artificial lights. Therefore, the annual electricity consumption of lighting system within the testing area (Q_{el-l}) can be computed by Eq. (4):

$$Q_{el-l} = \sum_{n=1}^{N} (T_{el-l} \times P_{lit})_n \tag{4}$$

where $n = 1, 2, \ldots, N$ is the number of the artificial lights in the testing area; P_{lit} is the power of each artificial light.

4.2.2. Thermal performance simulation

In this study, thermal performance is evaluated based on monthly heating and cooling load devoted for maintaining the thermal neutrality inside a building. The monthly heating and cooling load has to be calculated by thermal simulation engine in the BIM-based simulation system. Then the annual heating and cooling load is the sum of those in twelve months. Since one of the aims in this study is to reduce the LCCE of building designs, the thermal performance is evaluated by the amount of electricity consumed by the HVAC system to maintain the thermal neutrality. Hence, the coefficients of performance (COPs) for the heat pump and chiller has to be collected [34]. COP is the ratio of heating or cooling load provided over the consumed electrical energy. Consequently, annual electricity consumed by the thermal system (Q_{el-t}) can be figured out by Eq. (5):

$$Q_{el-t} = Q_{cool}/COP_{cool} + Q_{heat}/COP_{heat} \tag{5}$$

where Q_{cool} and Q_{heat} are the cooling load and heating load per year; COP_{cool} and COP_{heat} refer to COPs for chiller pump and heat pump respectively.

4.2.3. Output of BIM-based simulation system

When a series of simulations are completed, annual energy demand (AED) of lighting and thermal systems can all be figured out. As seen in Eq. (6), the total AED of the building design (Q_{el-s}) is a sum of the AED in the two parts above.

$$Q_{el-s} = Q_{el-l} + Q_{el-t} = \sum_{n=1}^{N} (T_{el-l} \times P_{lit})_n + Q_{cool}/COP_{cool} + Q_{heat}/COP_{heat} \tag{6}$$

4.3. PSO-based optimization system

In this section, a revised multi-objective particle swarm optimization (MOPSO) method is applied for building design scheme optimization. Detailed procedures are introduced as follows.

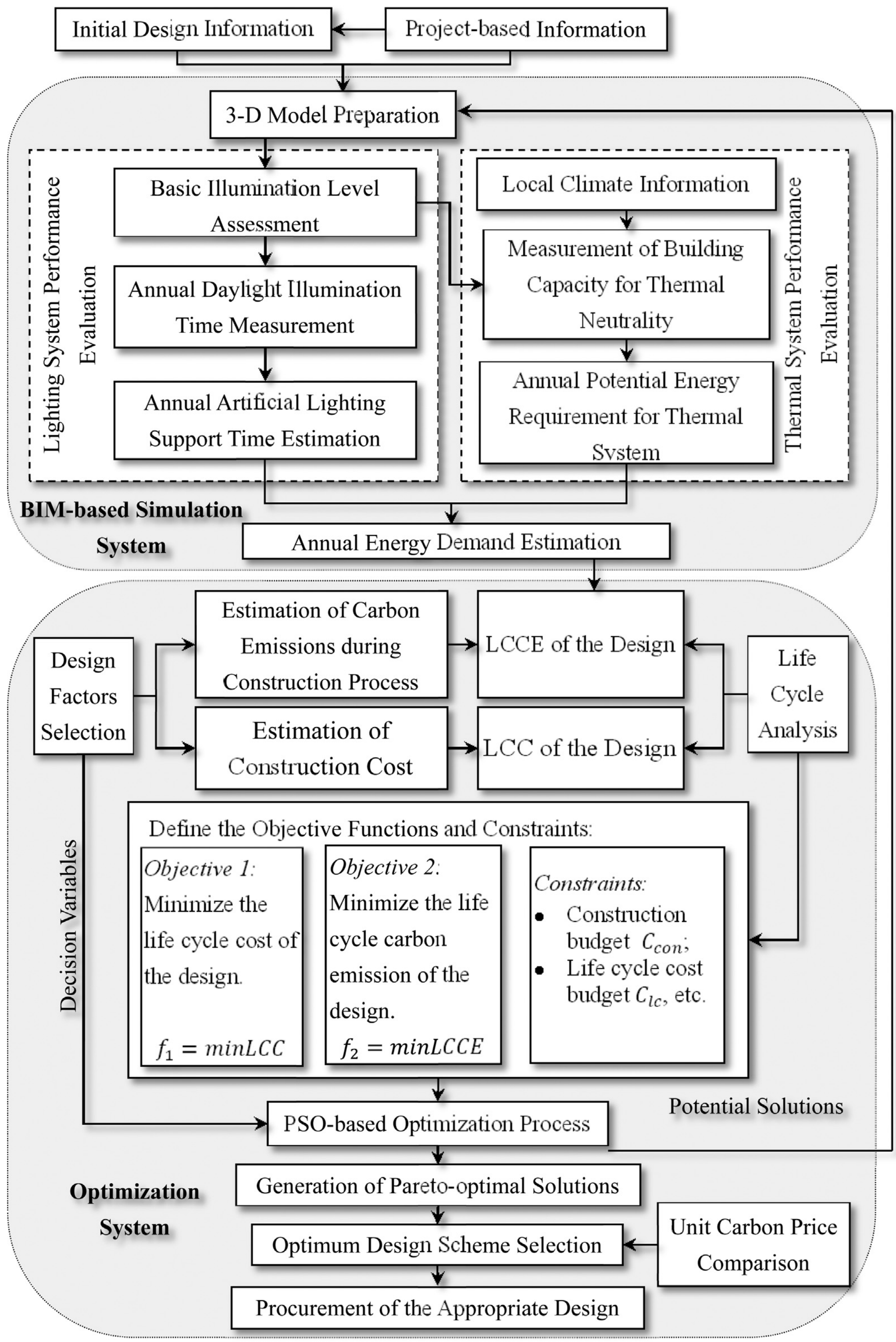

Fig. 2. Schematic structure of the proposed BIM-based building design optimization strategy for cost and carbon emission trade-off.

4.3.1. Preparations

After receiving the output from BIM-based simulation system, the optimization system searches for the optimal designs. Before it operates, some necessary parameters need to be preset.

As an important component in the optimization methods, decision variables have to be carefully selected. Important design factors which have major impacts on thermal and lighting systems are set as decision variables. Based on the review of many relevant studies [10,11,16,35,36,49], five decision variables: wall types, window-to-wall ratio (WWR), glazing types, external sunshade, and building orientation, are selected in this research. Building orientation is defined in this research as the angle between the east-west axis of the building and the North direction. Subsequent to the section of decision variables for the optimization system, objective functions can be worked out. Two objectives are generated for the optimization system: minimizing the LCCE and minimizing the LCC. This is a multi-objective optimization system, in which the optimal design gives the best trade-off between LCCE minimization and LCC minimization.

All the issues in the research scope should be counted in the two objective functions. To achieve this, a construction project has to be broken down into a number of work subsections by applying work breakdown structure (WBS). The details are illustrated in Fig. 3. Then the carbon emission and cost of the construction process can be calculated based on the work packages generated from WBS.

Since the cost and carbon emission are both calculated in the life cycle of buildings, the scope of life cycle has to be defined in this study. The life cycle of a building covers all the processes, including natural resource extraction, material production, construction, operation, maintenance and demolition. Maintenance and demolition are not considered in this study. It is because there are many uncertainties during the repair, recycle and disposal of materials, and meanwhile the corresponding data of environmental impact are not available for many assemblies and building materials [56]. As a result, processes included in the life cycle are enclosed by the dash lines in Fig. 4. Then the two objective functions can be calculated as follows:

- LCC:

$$LCC = C_{con} + C_{op} \tag{7}$$

where C_{con} is the construction cost of the building design scheme; C_{op} is the operation cost of the building design scheme.

Since LCC considers both the present and future cash flows as well as the time value of money [59], all of them need to be converted into present value (PV). As a result, the real LCC should be expressed as:

$$LCC = C_{con} + \sum_{t=1}^{T} (C_{op})_t \times (i+1)^{-t} \tag{8}$$

where $t = 1, 2, \ldots, T$ is the total number of years in the whole life cycle of a building; i is the interest rate for a compounding period.

Considering the inflation during the calculation period, the interest rate should be real interest rate. Eq. (9) shows the calculation method of real interest rate [37].

$$i = (i_n + 1)/(f + 1) - 1 \tag{9}$$

where i_n is the normal interest rate; f is the inflation rate.

- LCCE:

With the same components, the second objective function of LCCE can be expressed by Eq. (10):

$$LCCE = E_{con} + E_{op} \tag{10}$$

where E_{con} is the carbon emission of the construction process; E_{op} is the carbon emission of the operation phase of a building.

Since only the quantities of the resources devoted into the life cycle of a building design can be figured out by life cycle analysis, it is necessary to apply carbon emission factor (CEF) to compute the corresponding carbon emissions. CEF is the coefficient that represents the quantity of carbon dioxide and its equivalents emitted from one unit of a certain type of material. The CEFs vary depending on the types of materials. For electricity consumption, different generation modes lead to disparate CEFs. Nowadays, many databases have been established to provide the CEFs of hundreds of materials.

Table 1
The preset parameter values.

Parameter	Value
c_1	1.49445
c_2	1.49445
w_i	0.4
w_a	0.9
N	50
maxit	50
Anum	50
α	0.01
β	10
gridnum	50

Carbon emission is counted by multiplying the quantity of the resource with its corresponding CEF. Hence, the computing method of LCCE can be expressed as:

$$LCCE = \sum_{i=1}^{I} Q_i \times f_i + t \times Q_{el-s} \times f_{el} \tag{11}$$

where $i = 1, 2, \ldots, I$ is the number of the building material types; Q_i is the quantity of the ith material; f_i is the CEF of the ith material; f_{el} is the CEF of electricity.

The constraints in the optimization system are defined as: (1) both the construction cost and LCC cannot exceed their budget correspondingly; (2) the LCCE is hoped to be less than that of the initial design.

4.3.2. Optimization process

In this study, a revised MOPSO is employed to search for the optimal design scheme in the optimization system. In this method, a dependent archive is set to collect the best particles at each iteration in order to accelerate the computing speed. The roulette wheel selection method is deployed to determine the best global guide for each particle in this archive. The Gaussian mutation operator is also applied for avoiding fast local convergence. The operation approach of this algorithm is illustrated in Fig. 5.

Initially, the important control parameters need to be preset, which include cognitive parameter c_1 and social parameter c_2, minimum inertia weight w_i and maximum inertia weight w_a, population size N, maximum iteration number *maxit*, maximum repository size *Anum*, grid inflation parameter α, leader selection pressure parameter β, grid sum per dimension *gridnum*, etc. The values of them are shown in Table 1.

Inertia weight w mentioned in step 4 in Fig. 5 is a crucial parameter for the convergence of the particles in PSO method [60]. It is used to control the impact of the previous history of velocities on the present velocity of each particle. Selecting the inertia weight appropriately can provide a trade-off between global and local exploration abilities and therefore less iteration is needed to reach the Pareto-optimal front on average [24]. As a result, a linearly decreasing function is employed in this research to update the inertia weight which is shown as Eq. (12):

$$w = w_a - (w_a - w_i) \times iter / \max it \tag{12}$$

where *iter* is the number of the current iteration; *maxit* is the number of the maximum iteration.

When all the steps are completed, a set of Pareto-optimal solutions are obtained. Solutions in this set is non-dominated by each other, so designers have to select the one which mostly fulfill the requirements of the clients as the optimal design.

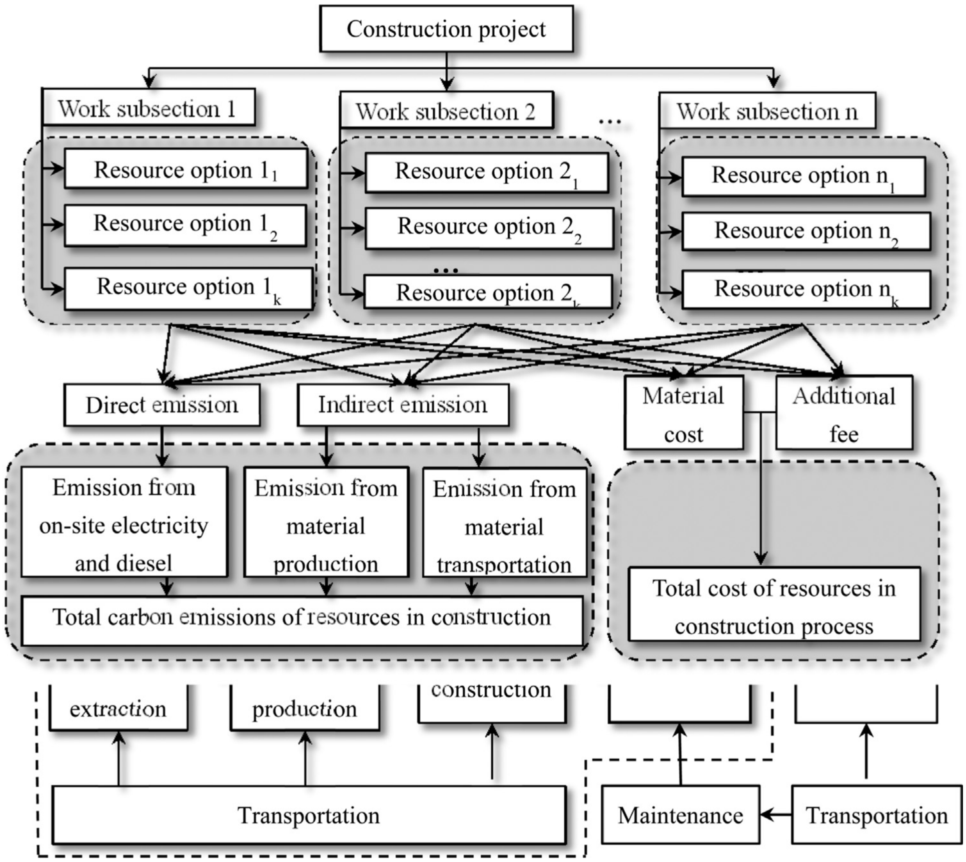

Fig. 3. WBS for carbon emission and cost estimation of construction process (modified from [54]).

4.3.3. Optimal design scheme selection

In order to get the "best" design which can meets most of the requirement of clients, a method called "Δ comparison" is proposed in this study.

Firstly, it is necessary to check whether the initial design is in the Pareto-optimal solution set. If yes, the decision maker can use the initial design directly. Otherwise, the selection process is operated as follows.

1) Calculate the Δ of each solution by Eq. (13):

$$\Delta_k = LCC_k / LCCE_k \tag{13}$$

where $k = 1,2,\ldots,K$ is the number of the solutions;

2) Sort the Δs in descending order, and then divide them into 3 levels, i.e. L_1, L_2, and L_3. The first $k/3$ solutions in the sequence are in L_1, the last $k/3$ solutions in the sequence are in L_3, and the rest are in L_2 (see Fig. 6).
3) Compare all the solutions with the initial design and then delete any one which has at least one fitness value (LCC and/or LCCE) larger than that of the initial design. For example, in Fig. 6, Solutions A, B and C have larger LCCE than the initial design, and Solution E has larger LCC than the initial design, so Solutions A, B, C and E are deleted.
4) Compare Δ_o with the Δ s in each level to see in which level the initial design falls.
5) For the Pareto-optimal front illustrated in Fig. 6, suggests that: although the solutions on the Pareto-optimal front are difficult to be judged as the "best", the ones located at the two extremes have the lower probability to be chosen as the optimal solutions, because the solutions located at the two extremes on the Pareto-optimal front has either too much LCC or too large amount of LCCE; thereby, they are less reasonable comparing with the ones located in the middle section. Based on this concept, the optimal design selection methods under the situations where the Δ_o falls in three levels are introduced respectively.

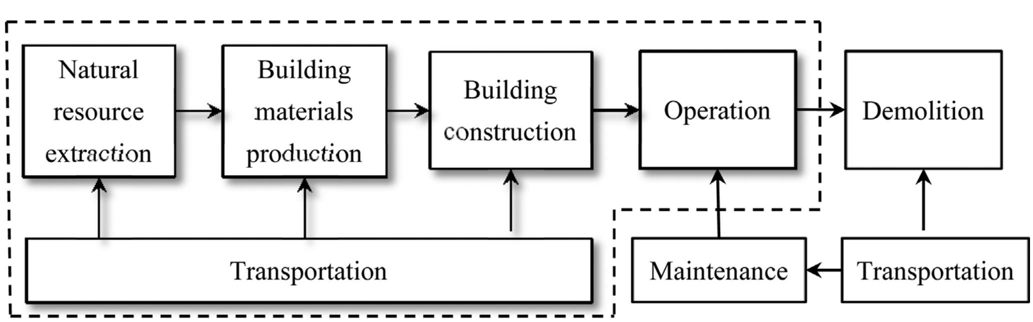

Fig. 4. Life cycle of buildings [56].

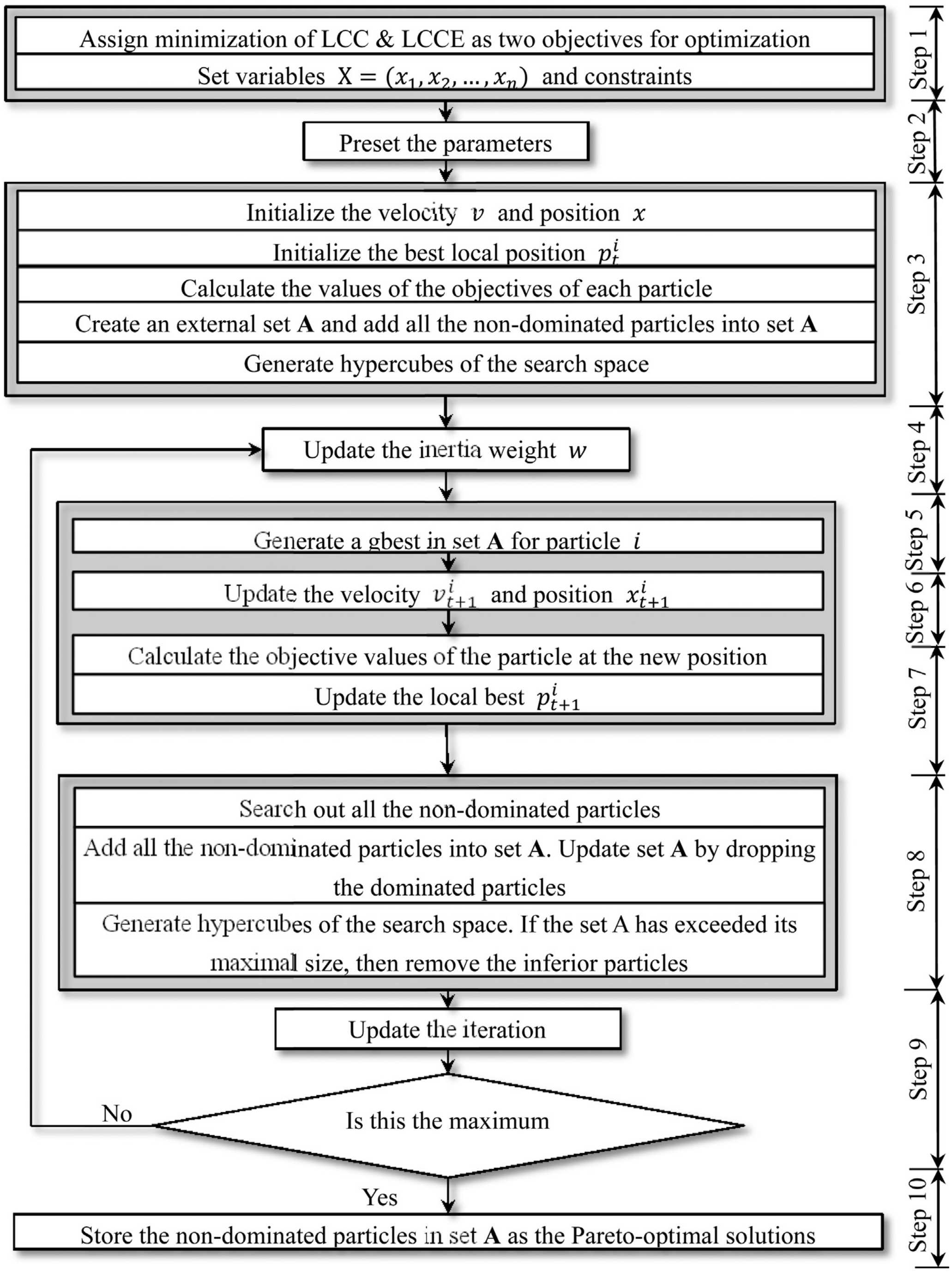

Fig. 5. The operation flow chart of PSO.

4.4. *Situation 1: Δ_o falls in L_1*

If Δ_o falls in level 1 (see Fig. 6), the optimal design solution is the one with least Δ_k in this level. For example, in the case shown in Fig. 6, Solution E should be selected as the optimal design scheme.

4.5. *Situation 2: Δ_o falls in L_2*

If Δ_o falls in level 2 (see Fig. 7), it is difficult to determine which one is better because they are all in the middle section of the Pareto-optimal front. So the distance between the origin of the coordinates and the solution has to be calculated. For the two objective functions, the fitness value of each objective function is the coordinate value of each solution, so the distance (D_k) can be calculated by Eq. (14):

$$D_k=\sqrt{(f_{1k})^2+(f_{2k})^2} \tag{14}$$

where, f_{1k} and f_{2k} are the fitness values of Objective Function One and Objective Function Two of the kth solution respectively.

By comparing the distances of each solution in this level, the one with least D_k is the optimal design scheme. Obviously, Solution D is the optimal design scheme in Fig. 7 because D_D is smaller than D_C.

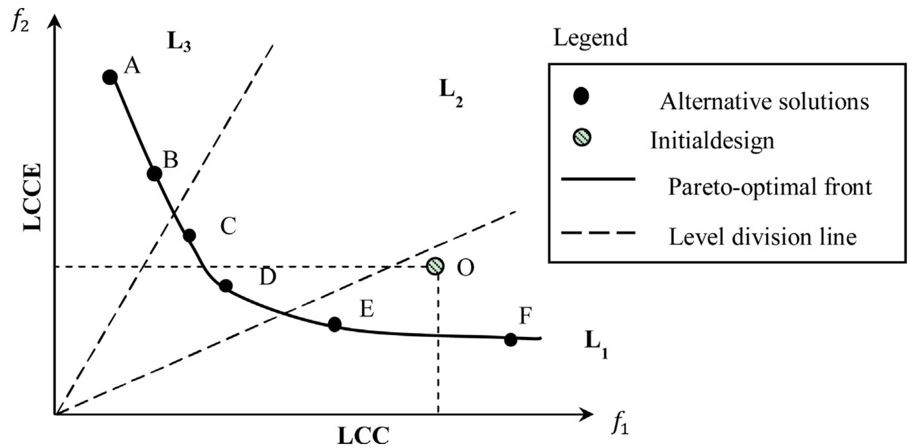

Fig. 6. Illustration of optimal design procurement method situation 1.

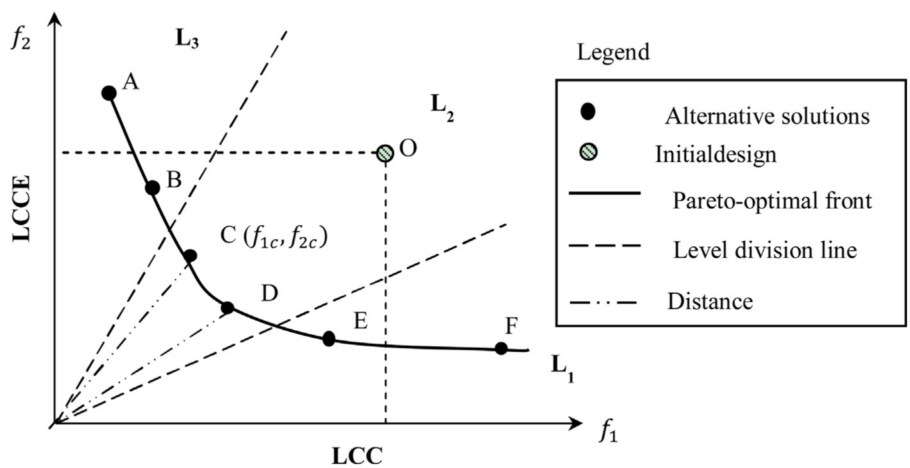

Fig. 7. Illustration of optimal design procurement method situation 2.

4.6. Situation 3: Δ_o falls in L_3

If Δ_o falls in Level 3 (see Fig. 8), the optimal solution is the one which has the largest Δ_k in this level. For instance, in Fig. 8, Solution B is the one that has the largest unit carbon price in Level 3, so it is the optimal design scheme.

By applying the Δ comparison method, the most appropriate building envelope design scheme can be figured out as the ultimate output of the optimization system.

5. Case study

5.1. Preparations

In order to validate the effectiveness and efficiency of the proposed BIM-based building design optimization method, a case study is conducted in this research. The case is an office building located in Kowloon, Hong Kong, with the gross floor area of 14,435.694 m^2. There are 10 floors in this building. The first and second floors are used as the entrance, storage and parking area. They are not considered in this research. The rest of the building is used as offices. The floor-to-roof height is 4.2 m, and distance between the floor and the false ceiling is 2.45 m. Fig. 9 shows the outline of the typical floor. The dark places in this figure are designed as open corridors and open balconies, which are not calculated. Moreover, the aluminum external sunshades are deployed above the windows in the open corridor and balcony areas, so all of them are located in the dark area in this figure. There are only three tiny windows: one in the staircase near to the floor and two in the washrooms close to the ceiling. They are arranged at Side A of the building envelope because this side has a very short distance to the adjacent building, so very few daylighting can be introduced into the indoor area. Besides, the rooms at Side D_2 in this case study are used as staircase and washrooms where the window arrangement is the same as that of Side A. For this reason, the design optimization of windows does not take Side A and Side D_2 into consideration. The study period of lifetime of the building is 50 years. Detailed information about the initial building design is listed in Table 2.

In order to apply the proposed method, two assumptions have to be made: (1) the only energy source used during the operation

Table 2
The initial design information of the case.

Design Factor		Content
Wall type		150 mm thick reinforced concrete wall + 15 mm thick cement and sand (1:3) screed + 15 mm internal plaster
WWR	Side *B*	0.441
	Side *C*	0.425
	Side D_1	0.462
Glazing type		8 mm thick clear float glass
External sunshade		65 mm thick, 600 mm wide, aluminum
Building orientation		280°

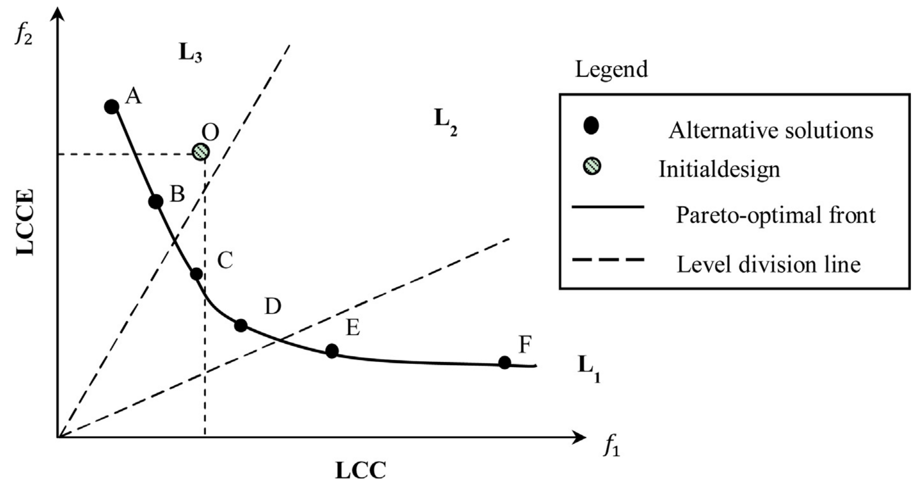

Fig. 8. Illustration of optimal design procurement method situation 3.

phase is electricity; (2) it is assumed that all the building materials are bought from the neighbor areas, i.e. Guangdong Province and Hong Kong. Meanwhile, the electricity rate does not change with seasons. In this study, only the typical floor of the case is selected as a representative for the simulation and optimization.

Following the procedures described above, a 3-D building information model is built in *Ecotect* with an analysis grid set at the work plane 750 mm high above the floor. There are a total of 250 testing points in the analysis grid. The file of weather data of Hong Kong is downloaded from the database provided by the U.S. Department of Energy (DOE).

The decision variables used in this case study is listed in Table 3. All the information of the unit prices of the building materials are collected from Alibaba.com, [47], the Census and Statistics Department of HKSAR, and GZZJ [38]. The CEFs are provided by Leung et al. [39] and Chen et al. [40].

All the alternatives and scopes of the decision variables are determined according to the project-based information provided by the project owners and the initial designs from the designers. For the wall types and glazing types, the first alternatives are from the initial designs. Since the walls of the buildings in Hong Kong only have the waterproof layers, their alternatives do not include any thermal insulation materials. Table 3 only shows the different parts of the wall type alternatives, and all the components of the external walls are designed in the following way (outside-in):

W + 15 mm thick cement and sand (1:3) screed + 15 mm thick internal plaster.

In this case study, locations of the windows does not change, so adjusting the height of the windows proportionally is the only way of changing the WWR. The distance between the external sunshade and the top of the window also does not change, which means that the location of the external sunshade alters with the change of the WWR. This assumption supposes that the external sunshade takes effect no matter how much the WWR changes. Additionally, detail information of the glazing types is shown in Table 4.

Aluminum is the material used for the external sunshade. The thickness listed in the initial designs is for the external sunshade, which is fixed during the optimization. The width of sunshade is the factor waiting for optimization. The largest width is designed up to 1.5 m. On the other hand, “0 m” means the external sunshade not being designed for the building.

Before the start of simulation, several types of parameters have to be predefined so that *Ecotect* can well mimic the real world conditions during the simulation process.

Fig. 9. Outline of the typical floor plan of the case.

5.2. Time schedule

In order to ensure that the electricity consumptions are estimated precisely, time schedules of this building have to be confirmed. For office buildings, people only use the building during working hours. So both the thermal system and lighting system are only operated during the working hours. In this study, the working days are set to be from Monday to Friday, and the working hours are from 9:00 a.m. to 18:00 p.m. in the whole year.

5.3. Thermal system

The climate of Hong Kong is sub-tropical. The average monthly temperatures over half a year is above 25 °C. This kind of climate means that the cooling activities dominate the thermal system in most of the buildings, especially in office buildings. So heating system is not included in this case. The cooling device is selected to be water-cooled chiller with the COP of 4.7, and the indoor design temperatures are 22 °C in winter and 23 °C in summer without night setback or setup [34].

Table 3
List of decision variables for the case.

Decision variable		Content	Unit price (HKD/m^2)	CEF (kg CO_2/m^2)
Wall Type	W_1	150 mm reinforced concrete wall	417.36	131.789
	W_2	150 mm aerated concrete block wall	318.24	70.857
	W_3	150 mm lightweight brick wall	392.16	252.473
WWR		α	[0.1, 0.8]	
Glazing type	G_1	Single clear glass	1600	128.672
	G_2	Double clear glass	2848.94	164.024
	G_3	Double low-e glass	3478.04	166.544
	G_4	Double tinted glass (green)	3425.18	164.960
	G_5	Tinted (green) and low-e glass	4096.30	167.480
Width of sunshade	b	[0,1.5] (unit: m)	23.63	227.340
Building orientation	θ	[0,360]		

5.4. Lighting system

It is assumed that all the lights used in this case study are T8 fluorescent tubes. The power of each light tube is 40 W. The occupancy sensing mode of the lighting control is selected to be manual, which means that the lights are opened by people when the illumination inside the building becomes lower than 500lux. All of them are turned off at the end of the working hours.

5.5. Others

The CEF of the electricity depends on the electricity generation mode. The electricity used in this case study is supported by CLP (China Light and Power Hong Kong Limited), according to which the CEF is 0.77 kg CO_2/kWh and the electricity tariff is 0.987 HKD/kWh.

In accordance with the Trading Economics [48], the average inflation rate in Hong Kong is 4.59% and the average normal interest rate is 4.06% in the period from 1998 to 2013. The real interest rate used in this case can be calculated by Eq. (9), and the result is −0.507%. Based on the interviews with the project owners and the financial information of the projects, the maximal construction cost is determined as HKD 5 million, and the maximal LCC is HKD 95 million.

The values of the parameters required in the optimization system are preset in Table 1. The computer used for the analysis is running with the Intel Core2 Duo CPU using a 32-bit Windows 7 operating system.

5.6. Operation of the proposed model

When all the preparations are ready, the whole system is run to generate the best design scheme.

First, according to the initial design information and project-based information, the building information model is established. The simulation system is run once to examine the lighting performance and thermal performance of the initial design. The results are used to compare with those of the optimal design scheme at the last step.

Second, the output of BIM-based simulation system is delivered to the optimization system. The optimization program is run once to generate a number of potential solutions randomly. These potential solutions are exported back to the simulation system. One design is read at one time and converted into a 3-D building information model. The lighting and thermal simulations then start to estimate the AED. The result is sent to the optimization system. When this procedure is finished on one solution, the simulation system repeats it on the next one until all the potential solutions are completed.

After receiving the AED, the optimization system has to compute the fitness values of objective functions for each particle, and follow the steps to find the non-dominated solutions for the current iteration. Then the next iteration starts and repeats the steps described above. When all the iterations run out, the Pareto-optimal solution set can be obtained. Afterwards, the initial design is compared with these optimized solutions. The ultimate optimum sustainable building design can be selected by means of Δ comparison method.

5.7. Results

Under the interactions between the simulation system and optimization system, the Pareto-optimal front is generated (see Fig. 10). The details of optimal solutions are listed in Table 5.

When getting the Pareto-optima solutions, the optimal design scheme has to be picked out with the help of Δ comparison method. Details are introduced as below.

Δ of each solution is calculated by Eq. (13), and the results are listed in Table 6.

Based on the Δs, solutions are divided into three levels. Table 7 shows the components of each level.

The LCC and LCCE of initial designs are compared with those of the potential solutions. All the solutions have less LCCs and LCCEs than the initial design, all of them are kept.

Fig. 11 shows the location of the initial design and potential solutions in the searching area. It reveals that the initial design falls in level 2.

At this step, the optimal design scheme can be figured out. The initial design is located in level 2, so the distances between the positions of the solution and the coordinate have to be calculated. The distances are: 353.466 for D_4; 357.831 for D_5; 362.325 for D_6; and 375.743 for D_7. Consequently, the fourth solution is selected to be the ultimate optimal design. Detail information of the optimal design is listed in Table 8.

Table 4
Detail information of the glazing alternatives.

Glazing type	Composition	U-value (W/m^2 K)	SHGC
G_{B1}	8 mm clear glass	5.39	0.85
G_{B2}	8 mm clear glass + 10 mm air gap + 8 mm clear glass	2.68	0.75
G_{B3}	8 mm clear glass + 10 mm air gap + 8 mm low-e glass	1.72	0.44
G_{B4}	8 mm tinted glass (green) + 10 mm air gap + 8 mm clear glass	2.68	0.56
G_{B5}	8 mm tinted glass (green) + 10 mm air gap + 8 mm low-e glass	1.72	0.42

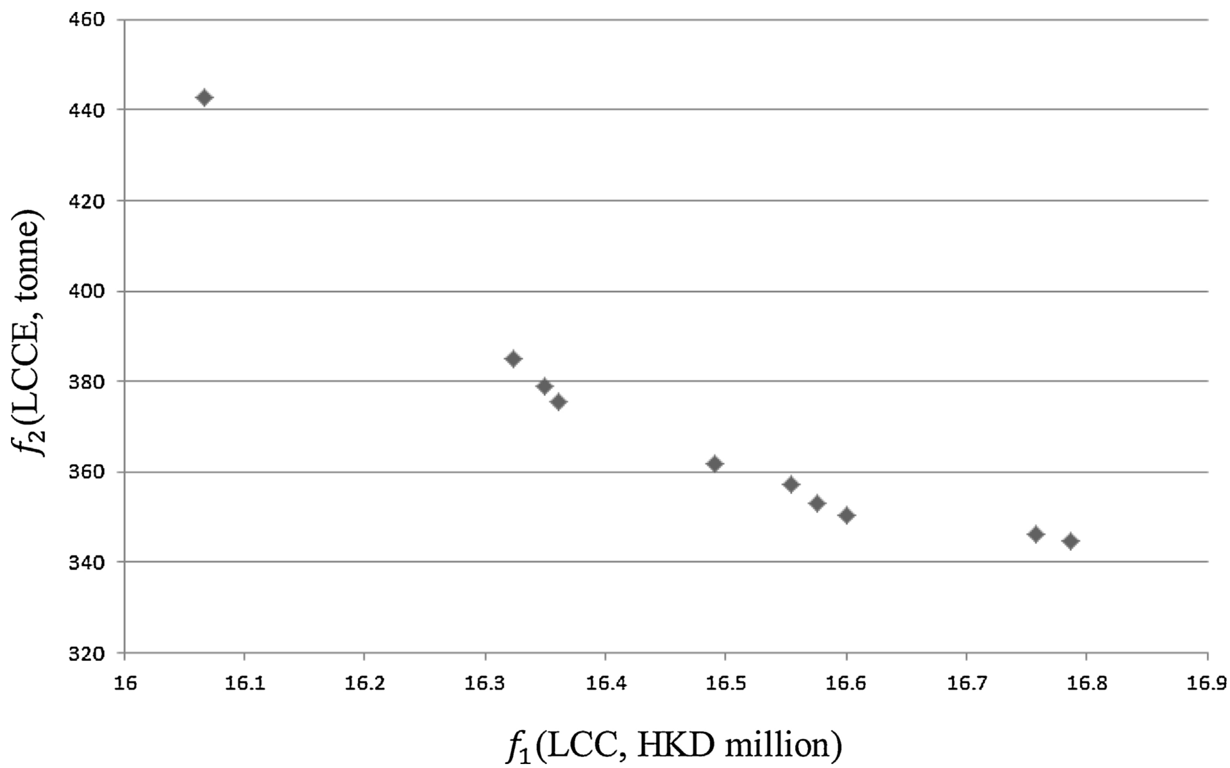

Fig. 10. The Pareto-optimal front of case study.

Table 5
Pareto-optimal solutions.

Solution	Wall type	WWR			Width of sunshade (m)			Glazing type	Building orientation (°)	LCC (HKD million)	LCCE (ton)
		$\propto_B$	$\propto_C$	$\propto_D$	b_B	b_C	b_D				
1	W_{B2}	0.151	0.402	0.108	0.152	0.463	0.507	G_{B1}	203	16.786	344.600
2	W_{B2}	0.405	0.047	0.456	1.208	0.149	0.133	G_{B1}	170	16.757	346.090
3	W_{B2}	0.580	0.201	0.337	1.180	0.167	0.186	G_{B3}	164	16.600	350.362
4	W_{B2}	0.674	0.033	0.373	1.359	0.107	1.120	G_{B3}	277	16.577	353.078
5	W_{B2}	0.432	0.232	0.500	1.073	1.326	0.248	G_{B3}	288	16.555	357.448
6	W_{B2}	0.641	0.754	0.311	0.547	1.330	0.214	G_{B4}	223	16.490	361.950
7	W_{B1}	0.277	0.624	0.130	0.845	0.046	1.191	G_{B2}	146	16.361	375.387
8	W_{B1}	0.156	0.681	0.561	0.233	1.160	0.566	G_{B5}	49	16.350	379.069
9	W_{B1}	0.031	0.648	0.297	1.351	0.952	1.337	G_{B2}	200	16.323	385.177
10	W_{B3}	0.511	0.196	0.246	0.137	1.047	0.399	G_{B4}	157	16.067	442.909
Initial	W_{B1}	0.321	0.325	0.313	1.5	1.5	1.5	G_{B1}	280	23.623	507.593

Table 6
The Δs of the Pareto-optimal solutions.

No.	Unit carbon price (million HKD/t)	No.	Unit carbon price (million HKD/t)
Δ_1	0.0487	Δ_6	0.0456
Δ_2	0.0484	Δ_7	0.0436
Δ_3	0.0474	Δ_8	0.0431
Δ_4	0.0469	Δ_9	0.0424
Δ_5	0.0463	Δ_{10}	0.0363

6. Discussion

6.1. Comparison with the initial design

In order to prove the effectiveness of the proposed BIM-based building design optimization method, the optimal design is compared with the initial design. The LCC and LCCE of the new design can be reduced by 29.83% and 30.44% respectively. The significant reduction in costs and carbon emissions demonstrates that the building envelope design optimization strategy proposed in this study is valid. Based on the significant reduction, the new design generated from this strategy satisfies the requirements of project owners and the environment.

6.2. Sensitivity analysis

Although the optimal design scheme has been well developed, it has to be verified in order to ensure its stability and reliability.

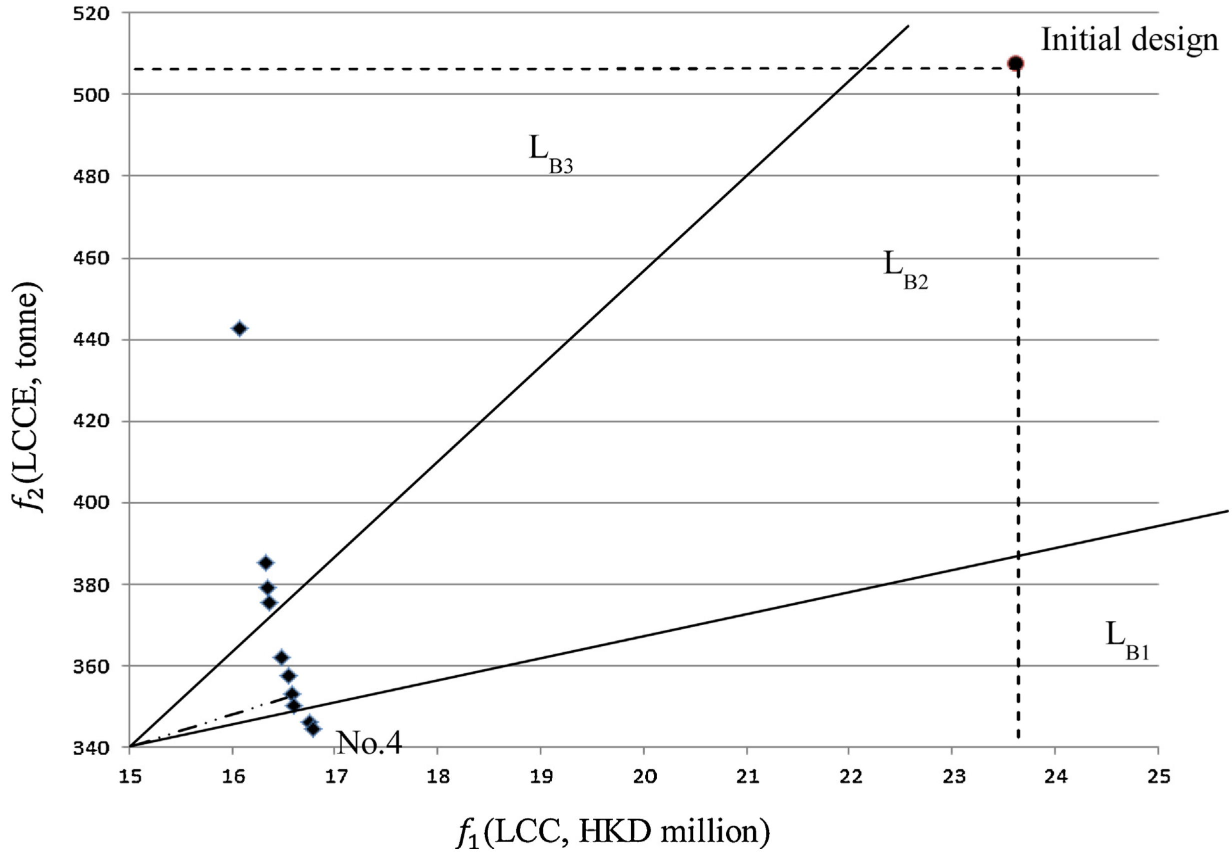

Fig. 11. Δ comparison between potential solutions and initial design.

Table 7
Levels division of the case study.

Case B	
Level	No. of solutions
L_{B1}	1, 2, 3
L_{B2}	4, 5, 6, 7
L_{B3}	8, 9, 10

Sensitivity analysis is applied for the verification: several alternative values of all these decision variables are collected one by one to replace their corresponding original values in the optimal design. Only one value of a decision variable is changed each time. The LCC and LCCE of the changed design is calculated and compared with those of the optimal design. At last, the percentages of the changes are counted to see whether the optimal design is affected by the changes in these decision variables.

The results show that, any variation of a decision variable can lead to the increase of the LCC and LCCE. This means that the final optimal design scheme is the best one in the sensitivity analysis range. Additionally, the change range of the decision variables is set to be −20%–20% which is wide enough for the real projects, so the optimal design generated from the proposed strategy proves stable and reliable.

6.3. *Applicability of the proposed BIM-based building design optimization method*

The proposed building design optimization method is composed of a BIM-based simulation system and an optimization system. The optimal design is generated by the interactions between these two systems. Sensitivity analysis on the results of the case study provides the reliability for the proposed method. Meanwhile, it demonstrates that the final optimal building design scheme is the best in a wide range of searching space. Clearly, this optimization method is effective.

In addition, the operation time of this method in the case study is around 104 h. It is assumed that all the decision variables are discrete, the values of WWR and width of sunshade are accurate to the first decimal place, and the value of building orientation is accurate to units. Thus, a total of 5,832,000 potential solutions are generated in the case study. If 5 min is used for checking one solution, then it requires 486,000 h to assess all the solutions. By comparison, the

Table 8
The optimum building design scheme.

WWR			Width of sunshade		
$\propto_B$	$\propto_C$	$\propto_D$	b_B	b_C	b_D
0.925	0.043	0.756	1.359	0.107	1.120

Glazing type	Building orientation	LCC (HKD million)	LCCE (ton)	Wall type
G_3	277°	16.577	353.078	W_2

processing time in this study only accounts for 0.21‰ of that in the traditional ways.

Traditional building design methods usually use discrete variables. As a result, the searching scope is narrowed down. Unlike the traditional design methods, the proposed method in this study can deal with continuous design factors. It has several advantages: (1) important continuous design factors can be optimized so that the design schemes are more effective and reliable; (2) the traditional problem mentioned above can be solved by the proposed method, in which the searching scope can be defined as large as possible; (3) the proposed method allows designers to set the precision of the values as high as possible, which is necessary for improving the reliability of design optimization methods; and (4) both the lighting performance and thermal performance are taken into consideration at the same time, resulting in higher efficiency and effectiveness in the design process.

With the help of BIM, every detail of designs can be visible via 3-D model; designers can check the reasonability and mistakes of designs visually. All the information of designs is saved in the database of BIM, designers and clients can search for anything they need from the database whenever they want, which saves much time and manpower. In addition, the simulation engine is preset in BIM, so the data of building performance can be directly saved, which solves the trouble of data transmission between two programs. All the information of designs in BIM can be used for the following steps of the project, i.e. the construction and operation of buildings. It means that with the selection of the optimum design scheme, all the files and data required by the construction contractors and clients are completed in BIM as well.

7. Conclusion

This study proposes a BIM-based building design optimization method with the aim of improving the sustainability of buildings. It achieves its aim and objectives by integrating BIM-based simulation system and PSO-based optimization system. A case study has proved its reliability, effectiveness and efficiency. Comparing with the traditional design methods, this study can consider multi-objective problems (i.e. LCC minimization and LCCE minimization). The application of life cycle analysis gives designers and clients a general view of their projects and increases the probability of being successful. When using the proposed method, continuous and discrete factors can be processed together so that the searching scope is enlarged. Hence, many more optimal designs can be generated. In addition, both thermal system and lighting system are assessed in the proposed method so that the design process can reflect their interaction. Therefore, the results are much closer to the real world situations. Finally, all the procedures are completed by coding programs and software in PC, which can reduce the workload of designers and avoid their errors and mistakes. As a result, designers can obtain the optimal designs faster and easier. All these will help to improve the development of sustainable buildings.

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